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Portfolio Allocation: Getting the most out of realised volatility

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Abstract

Recent advances in the measurement of volatility have utilized high frequency intraday data to produce what are generally known as realised volatility estimates. It has been shown that forecasts generated from such estimates are of positive economic value in the context of portfolio allocation. This paper considers the link between the value of such forecasts and the loss function under which models of realised volatility are estimated. It is found that employing a utility based estimation criteria is preferred over likelihood estimation, however a simple mean squared error criteria performs in a similar manner. These findings have obvious implications for the manner in which volatility models based on realised volatility are estimated when one wishes to inform the portfolio allocation decision.

Keywords
Volatility, utility, portfolio allocation, realized volatility, MIDAS

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1 Introduction

Forecasts of volatility are important inputs into numerous financial applications, including derivative pricing, risk estimation and portfolio allocation. The modern volatility forecasting literature stems from the seminal work of Engle (1982) and Bollerslev (1986) in a univariate setting, and from Bollerslev (1990) and Engle (2002) among others in the multivariate setting. For a broad overview of the major developments in this field, see Campbell, Lo and MacKinlay (1997), Gourieroux and Jasiak (2001) and Andersen, Bollerslev, Christoffersen and Diebold (2006).

In recent years there have been many developments in the measurement of volatility by utilizing high frequency intraday data, a principle stemming from the earlier work of Schwert (1989). Andersen, Bollerslev, Diebold and Labys (2001, 2003) and Barndorff-Nielsen and Shephard (2002) among others advocate the use of realised volatility as a more precise estimate of volatility relative to those based on lower frequency data[1]. Fleming, Kirby and Ostdiek (2003) highlight the positive economic value of realised volatility relative to estimates of volatility based on daily returns. They do so in the context of a risk-averse investor using mean-variance analysis to allocate wealth across asset classes.

While there is no doubt that realised volatility offers a superior estimate of volatility, little is understood of how best to estimate models based on realised volatility. Traditionally, volatility models such as GARCH models, along with those based on realised volatility are estimated by quasi-maximum likelihood (QML). Parameter estimates obtained under a QML loss function are used to subsequently generate forecasts applied in the portfolio allocation context, see Fleming, Kirby and Ostdiek (2001, 2003). Skouras (2007) proposes a different approach in which a utility based metric is used to estimate the parameters of a univariate volatility model. Such an approach has much to recommend it as the criteria under which the model is estimated and then applied are consistent.

This paper considers how best (in terms of the choice of loss function) to estimate a model based on realised volatility used for the purposes of portfolio allocation. Within a portfolio allocation framework, this paper compares the performance of two models estimated by traditional statistical methods and a utility based criterion. A three asset, portfolio allocation problem involving equities, bonds and gold will be examined. The model chosen is the MIDAS approach of Ghysels *et al.* (2006)

It is found that the loss function under which the volatility model is estimated influences the

[1]Following Fleming, Kirby and Ostdiek (2003) we use the general realised volatility term to refer to the full realised covariance matrix of asset returns. In later sections, we refer specifically to variances, covariances and correlation

performance of its forecasts, and hence the value of realised volatility in a portfolio allocation setting. Performance here reflects the economic benefit of a forecast as measured by the utility produced by portfolios on the basis of the forecast. Of the two statistical approaches considered, estimation under a simple minimum mean squared error (MSE) criteria is preferred to QML estimation. Utility based estimation is also preferred over QML and performs in a very similar manner to MSE estimation. Variations in performance across the loss functions are consistent with properties of the loss functions discussed in subsequent sections.

The paper proceeds as follows. Section 2 outlines the general portfolio allocation framework, including how transactions costs may be incorporated along with how model performance will be compared. Section 3 outlines the volatility model considered and the competing loss functions under which estimation occurs. Section 4 outlines some important analytical properties of the utility based loss function to allow comparisons to drawn with the statistical loss functions. Section 5 describes the data employed and the associated empirical results. Section 6 provides concluding comments.

2 The portfolio allocation problem

We follow Skouras (2007) and consider an investor with negative exponential utility,

$$u(r_{p,t}) = -\exp(-\lambda\, r_{p,t}) \tag{1}$$

where r_p is the portfolio return realised by the investor during the period to time t and λ is their coefficient of risk aversion.

We assume the vector of excess returns $\boldsymbol{r}_t$ obey

$$\boldsymbol{r}_t \sim \boldsymbol{F}(\boldsymbol{\mu}, \boldsymbol{\Sigma}_t)\,, \tag{2}$$

where $\boldsymbol{F}$ is some multivariate distribution, $\boldsymbol{\mu}$ is fixed vector of expected excess returns and $\boldsymbol{\Sigma}_t$ is the conditional covariance matrix of returns. The manner in which the portfolio of risky assets will be constructed is now described.

Begin by defining $\overline{\boldsymbol{\Sigma}}_t$ as a forecast of the conditional covariance matrix, $\mathbf{w_t}$ as a vector of portfolio weights and μ_0 to be the target return for the portfolio. The composition of the optimal portfolio is then given by

$$\boldsymbol{w}_t = \frac{\overline{\boldsymbol{\Sigma}}_t^{-1}\boldsymbol{\mu}}{\boldsymbol{\mu}'\overline{\boldsymbol{\Sigma}}_t^{-1}\boldsymbol{\mu}}\,\mu_0\,. \tag{3}$$

Portfolio returns are then determined by $r_{p,t} = \boldsymbol{w}_t'\boldsymbol{r}_t$. The manner in which $\overline{\boldsymbol{\Sigma}}_t$ is obtained is described in the following section.

We follow Fleming, Kirby and Ostdiek (2001, 2003) in comparing the performance of the various estimation criteria in terms of the relative economic benefit they produce when forming portfolios from their resultant forecasts. We find a constant, Δ that solves

$$\sum_{t=1}^{T} U(r^1_{p,t}) = \sum_{t=1}^{T} U(r^2_{p,t} - \Delta) \tag{4}$$

where $r^1_{p,t}$ and $r^2_{p,t}$ represent portfolio returns based on two competing estimation criteria. Here Δ reflects the incremental value of using the second approach as opposed to the first. It measures the maximum return an investor would be willing to sacrifice, on average per day, to capture the gains of switching to the second criteria. Δ will be reported in annualized basis points below.

In practice, an investor will incur transaction costs as they alter their portfolio as a result of changes in the optimal portfolio allocation to equity, and or, bond futures stemming from equation (3). An investor will experience costs from trading, which we assume here to reflect the bid-ask spread. This cost is approximated by $\frac{\text{Bid-ask spread}}{\text{Futures Price}}$ where the bid-ask spread quoted in index points. We assume this cost is paid by the investor as the optimal allocation changes through time. Assuming an arbitrarily large investment portfolio (or infinitely divisible contracts) the transaction costs are given by

$$tc_t = |w_t - w_{t-1}| \frac{\text{Bid-ask spread}}{\text{Futures Price}}. \tag{5}$$

for each individual futures contract. Total cost is due to changes in both bond and equity exposure.

This scheme is applied across all models, estimated under the statistical or economic criteria by augmenting the expression for realized utility in equation (1),

$$u(r_{p,t}) = -\exp(-(\lambda\, r_{p,t} - tc_t)) \tag{6}$$

prior to comparing the estimation criteria using equation 4. This approach provides a post-transactions cost measure of the economic value of each of the estimation criteria.

3 Forecasting the covariance matrix

The approach for generating a forecast of the covariance matrix, $\overline{\mathbf{\Sigma}}_t$ is drawn from the family of MIDAS regressions. This methodology produces volatility forecasts directly from a weighted average of past observations of volatility. This approach is chosen as it is simple to estimate and there is a clear link between the estimated parameters and manner in which historical data is weighted.

Following from Ghysels *et al.* (2006) a forecast of the conditional covariance matrix, $\overline{\boldsymbol{\Sigma}}_t$ is generated by

$$\overline{\boldsymbol{\Sigma}}_t = \sum_{k=1}^{k_{\max}} b\left(k, \boldsymbol{\theta}\right) \widehat{\boldsymbol{\Sigma}}_{t-k} \tag{7}$$

where $\widehat{\boldsymbol{\Sigma}}_{t-k}$ are historical observations of the realized covariance matrix. In this instance, the same MIDAS weights, $b\left(k, \boldsymbol{\theta}\right)$ will be applied to all elements of $\widehat{\boldsymbol{\Sigma}}_{t-k}$. The maximum lag length $k_{\max}$ can be chosen rather liberally as the weight parameters $b\left(k, \boldsymbol{\theta}\right)$ are tightly parameterized. All subsequent analysis is based on $k_{\max} = 100$. Here the weights are determined by means of a beta density function and normalized such that $\sum b\left(k, \boldsymbol{\theta}\right) = 1$. A beta distribution function is fully specified by the 2×1 parameter vector $\boldsymbol{\theta}$. Here $\theta_1 = 1$ meaning that only the θ_2 must be estimated. The constraint $0 < \theta_2 < 1$ ensures that the weighting function is a decreasing function of the lag k. When θ_2 is close to 1 there is little decay in the weights and hence this weighting function is similar in nature to a simple moving average. However, as the value for θ_2 becomes smaller, more weight is placed on the most recent observations and less on the distant observations. The loss functions under which values for θ_2 in equation 7 is estimated will be described.

Quasi- Maximum Likelihood QML

The value for θ_2 is chosen so as to

$$\underset{\theta_2}{\operatorname{argmax}} \sum_{t=1}^{T} log(|\overline{\boldsymbol{\Sigma}}_t|) + \boldsymbol{r}_t \overline{\boldsymbol{\Sigma}}_t^{-1} \boldsymbol{r}_t'. \tag{8}$$

Minimum Mean Squared Error MSE

Under this estimation criteria, θ_2 is chosen so as to

$$\underset{\theta_2}{\operatorname{argmin}} \sum_{t=1}^{T} \operatorname{vec}(\overline{\boldsymbol{\Sigma}}_t - \widehat{\boldsymbol{\Sigma}}_t)' \operatorname{vec}(\overline{\boldsymbol{\Sigma}}_t - \widehat{\boldsymbol{\Sigma}}_t). \tag{9}$$

Utility Based Estimation UTL

Skouras (2007) proposes a method by which the parameters of a univariate volatility model can be estimated directly within an economic criteria. As opposed to likelihood maximization, Skouras (2007) suggests estimating parameters by maximizing the utility realized from the portfolios formed from model forecasts.

Given the optimal portfolio rule in equation (3), and the expression for realized utility in equation (1), the objective function for a maximum utility estimator is

$$\underset{\theta_2}{\operatorname{argmax}} \frac{1}{T} \sum_{t=1}^{T} - \exp(-\lambda \mathbf{w_t}' \boldsymbol{r}_t). \tag{10}$$

Parameter estimation is conducted on the basis of optimally weighting historical volatility so as to construct portfolios that lead to the greatest expected utility as opposed to statistically optimal forecasts of volatility.

4 Some properties of the loss functions

Begin by defining $\boldsymbol{w}_t$ as the vector of weights generated from the true $\boldsymbol{\Sigma}_t$, $\overline{\boldsymbol{w}}_t$ as a vector of incorrect weights generated from $\overline{\boldsymbol{\Sigma}}_t$, and $\boldsymbol{c}_t$ as a vector of weighting errors $(\overline{\boldsymbol{w}}_t - \boldsymbol{w}_t)$ due to $\overline{\boldsymbol{\Sigma}}_t \neq \boldsymbol{\Sigma}_t$. $\boldsymbol{w}_t'\boldsymbol{\mu}_t = \mu_0$ and $\boldsymbol{w}_t'\boldsymbol{\mu}_t + \boldsymbol{c}_t'\boldsymbol{\mu}_t = \mu_0$ hence $\boldsymbol{c}_t'\boldsymbol{\mu}_t = 0$. The utility earned from using the forecast $\overline{\boldsymbol{\Sigma}}_t$ is

$$- \exp(-\lambda\, \boldsymbol{w}_t'\boldsymbol{r}_t + \boldsymbol{c}_t'\boldsymbol{r}_t) \tag{11}$$

whereas the utility earned from using the correct $\boldsymbol{\Sigma}_t$ is

$$- \exp(-\lambda\, \boldsymbol{w}_t'\boldsymbol{r}_t). \tag{12}$$

We wish to show the expectation of the difference between equations 12 and 11, ΔU (as a reflection of the loss in expected utility from $\overline{\boldsymbol{\Sigma}}_t \neq \boldsymbol{\Sigma}_t)^2$. To begin, the difference between equations 12 and 11 can be written as

$$- \exp(-\lambda\, \boldsymbol{w}_t'\boldsymbol{r}_t) \left[1 - \exp(-\lambda\, \boldsymbol{c}_t'\boldsymbol{r}_t)\right]. \tag{13}$$

Cochrane (2001) shows expected value of the exponential utility function defined over a generic variable y is

$$\mathbb{E}[\exp(-\lambda y)] = - \exp\left(-\lambda \mathbb{E}(c) + \frac{\lambda^2}{2}\sigma^2(c)\right). \tag{14}$$

Based on this rule the expectation of equation 13 leads to

$$- \exp\left(-\lambda\, \boldsymbol{w}_t'\mathbb{E}(\boldsymbol{r}_t) + \frac{\lambda^2}{2}\boldsymbol{w}_t'\boldsymbol{\Sigma}_t\boldsymbol{w}_t\right)\left[1 - \exp\left(-\lambda\, \boldsymbol{c}_t'\mathbb{E}(\boldsymbol{r}_t) + \frac{\lambda^2}{2}\boldsymbol{c}_t'\boldsymbol{\Sigma}_t\boldsymbol{c}_t\right)\right], \tag{15}$$

and as $\mathbb{E}(\boldsymbol{r}_t) = \boldsymbol{\mu}$ and $\boldsymbol{c}_t'\boldsymbol{\mu} = 0$, this simplifies to

$$- \exp\left(-\lambda\, \boldsymbol{w}_t'\mathbb{E}(\boldsymbol{r}_t) + \frac{\lambda^2}{2}\boldsymbol{w}_t'\boldsymbol{\Sigma}_t\boldsymbol{w}_t\right)\left[1 - \exp\left(\frac{\lambda^2}{2}\boldsymbol{c}_t'\boldsymbol{\Sigma}_t\boldsymbol{c}_t\right)\right]. \tag{16}$$

Equation 16 shows that a utility based estimation criteria shares some common features with MSE loss. Both loss functions will reach a minimum when $\overline{\boldsymbol{\Sigma}}_t = \boldsymbol{\Sigma}_t$, irrespective of the form of $\boldsymbol{F}(\cdot,\cdot)$ in equation 2. In the MSE case, equation 9 will take a value of zero, whereas the loss of utility shown in equation 16 will become zero as $\boldsymbol{c}_t$ will be a vector of zeros when $\overline{\boldsymbol{\Sigma}}_t = \boldsymbol{\Sigma}_t$. Hence the final term in square brackets will become zero. The $\boldsymbol{c}_t'\boldsymbol{\Sigma}_t\boldsymbol{c}_t$ term in equation 16 shows

[2] Assuming $\boldsymbol{c}_t$ and $\boldsymbol{r}_t$ are uncorrelated

that forecast errors leading to $\boldsymbol{c}_t$ reduce utility in a quadratic like manner, in a similar fashion to the quadratic MSE loss function.

Skouras (2007) highlights the difference between maximum utility estimators (UTL in this case) and those obtained under QML. QML based estimators minimize information criteria such as Kullback-Liebler which only corresponds to a maximal utility estimator in the case where there is no model mispecification. In the face of model mispecification, Skouras (2007) shows that the estimated parameters (and hence forecasts) form both approaches diverge and that QML will lead to lower realised utility. This suggests that one would expect forecasts generated from models estimated under QML loss will lead to inferior portfolios relative to those formed from forecasts based on maximum utility estimators. As the discussion above shows a similarity between the MSE and utility based loss functions, it is expected that MSE would produce similar forecasts and hence optimal portfolios in comparison to the utility based criteria.

5 Data and empirical results

The portfolio allocation problem considered here relates to a mix of bond, equities and gold. The study treats returns on the S&P 500 Composite Index futures as equities exposure, returns on U.S. 10-year Treasury Note futures as bond market exposure along with returns on Gold futures [3]. Data was gathered for the period covering 1 July 1997 to 29 June 2009 giving a sample of 2985 observations. Estimates of the daily conditional covariance matrix were constructed by summing the cross products of 15 minute futures contract returns.

Figure 1 plots the realized variance of equity futures (top panel), bond futures returns (middle panel) and gold futures returns (lower panel). Equity volatility shows a familiar pattern, low volatility during much of the sample period with higher volatility due to collapse of technology stocks. It is clear that the events surrounding the credit crisis of the second half of 2008 dominate in terms of the levels of volatility reached (the scale of the plot has been constrained otherwise no variation is evident due to the level of recent volatility). The volatility of bond returns is unsurprisingly much lower in magnitude than equity returns and generally more stable. It is evident that the recent financial crisis has lead to a sustained period of somewhat higher volatility. Volatility in gold returns rose in late 2005 and early 2006 due to central bank activity, and rose to historically high levels due the height of the recent market turmoil.

Realized correlations between the respective pairs of assets are shown in Figure 2. The correlation between equities and bonds (top panel) is quite persistent over time. It shows a downward trend through to 2002-2003 with it subsequently being weak during 2004-2006, followed by a

[3] Intraday data for both futures contracts were purchased from Tick Data

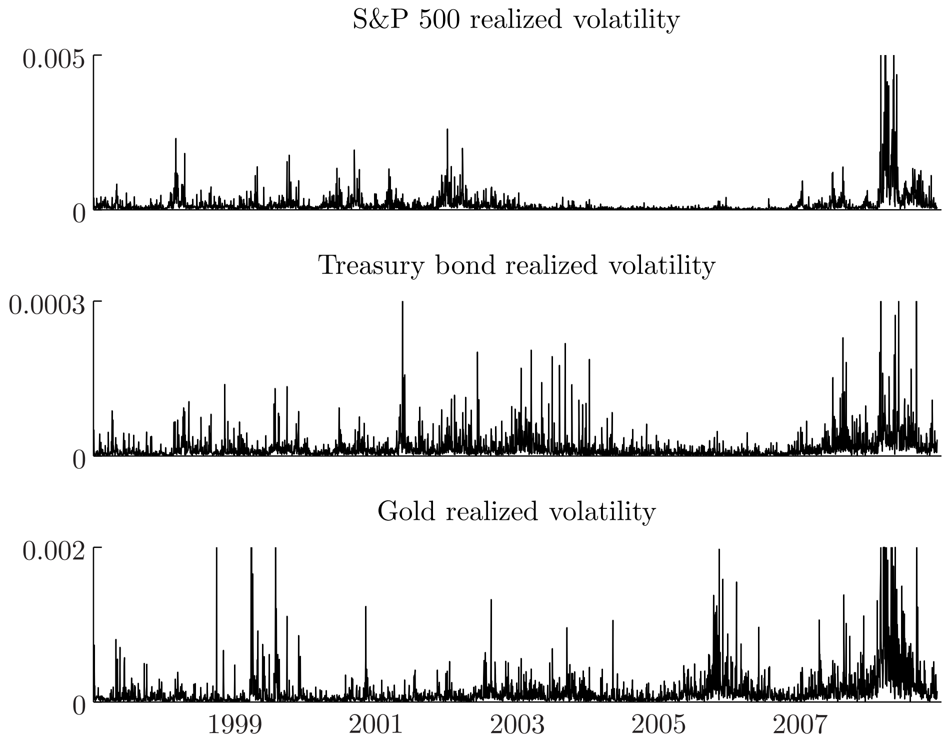

Figure 1: S&P 500 RV estimates (top panel), Treasury bond RV estimates (middle panel) and Gold RV estimates (bottom panel).

period very strong negative correlation during much of the recent crisis. In contrast to the bond and equity case, neither the correlation between either equities and gold (middle panel) nor bonds and gold (lower panel) show any long-term persistence or structure.

Given the 2985 daily observations, the first 1000 observations were used as an initial estimation period. One day ahead forecasts of $\overline{\boldsymbol{\Sigma}}_t$ are obtained for $t = 1001$ and a portfolio formed according to Section 2. This scheme is recursively repeated leading to 1985 estimates of θ_2, $\overline{\boldsymbol{\Sigma}}_t$ and subsequent portfolio allocations. The first sets of results discussed below are based on an expected return (shown in annualized percentage terms) vector of $\mu = [3.12; 2.69; -9.45]$ corresponding to the unconditional mean returns for equities, bonds and gold respectively for the initial 1000 observations. The target return was Set at $\mu_0 = 2\% \, p.a.$. In practice, there is great deal of uncertainty surrounding the level of the expected returns, this issue will be discussed later in this section.

We begin the discussion of the empirical results by considering the estimated θ_2 weighting parameter given each of the loss functions. Estimated values of θ_2 are always found to be close to zero under the QLK loss function, and one under UTL. This means that a quickly (slowly) decaying weighting scheme is preferred under QLK (UTL). Figure 3 shows the estimated value for each of the 1985 estimation periods given the MSE loss function. It is clear that while under

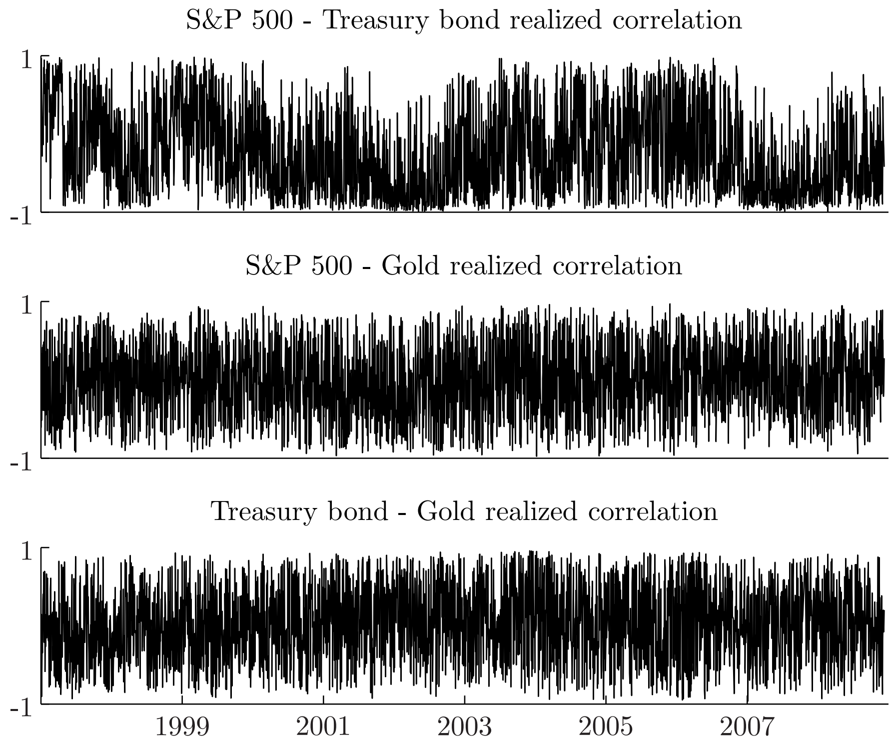

Figure 2: S&P 500 and RV Treasury bond realized correlation estimates (top panel), S&P 500 and Gold realized correlation estimates (middle panel) and Treasury bond and Gold realized correlation estimates (bottom panel).

MSE θ_2 fluctuates somewhat, it remains close to 1 much of the time and hence leading to a slowly decaying weighting scheme similar to UTL. Hence volatility model parameters estimated under MSE or UTL are very similar in contrast to QLK. The similarity between MSE and UTL, and differences relative to QLK are consistent with the discussion in Section 4 in that the MSE and UTL loss functions share common properties that differ to QLK.

Differences in the allocations to equity, bonds and gold implied by the loss function are shown in Figures 4, 5 and 6 respectively. In each instance, differences between the allocations implied by MSE and QLK forecasts are shown in the top panels, UTL and QLK in the middle panels and MSE and UTL in the lower panels. Overall, it can be seen that none of the loss functions generally lead to the same allocations, however there are short periods where both MSE and UTL produce virtually identical outcomes. A very striking result however is the relative magnitude of the differences. The lower panels for all three assets have a scale 10 times less than that of the higher panels. This clearly indicates that the resultant portfolios from MSE and UTL are much more similar in nature relative to QLK. This is consistent with the findings from Figure 3 in that the differences in weighting parameters lead to differences in forecasts of $\overline{\boldsymbol{\Sigma}}_t$. Similarity of the allocations under MSE and UTL is a reflection of the similarity in values for θ_2 shown

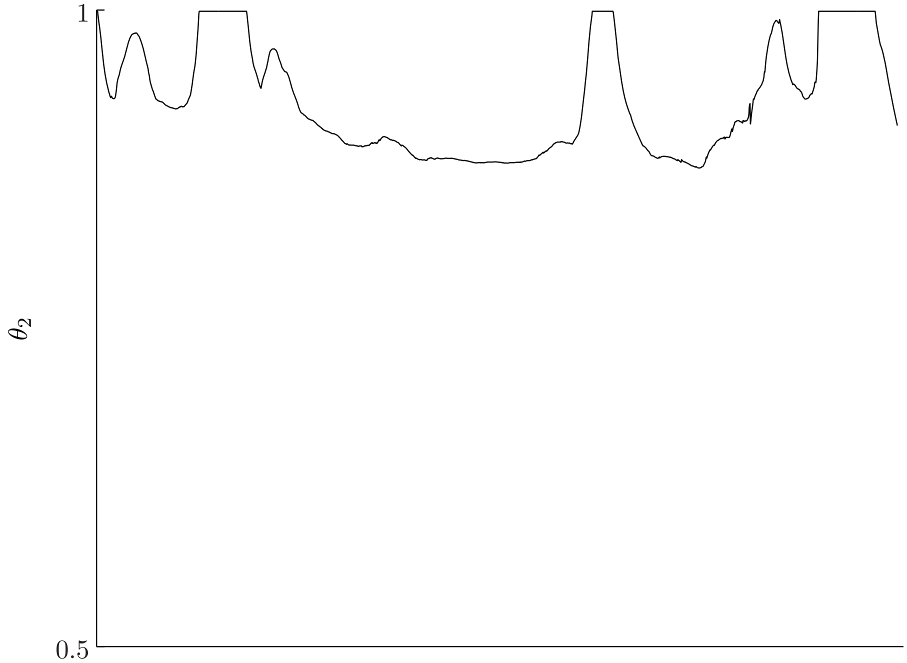

Figure 3: Estimated values for MIDAS weighting parameter, θ_2 under MSE.

in Figure 3. While not shown here, the portfolio allocations given MSE and UTL are much smoother than those due to QLK due to slower decay in the MIDAS weighting scheme under MSE and UTL.

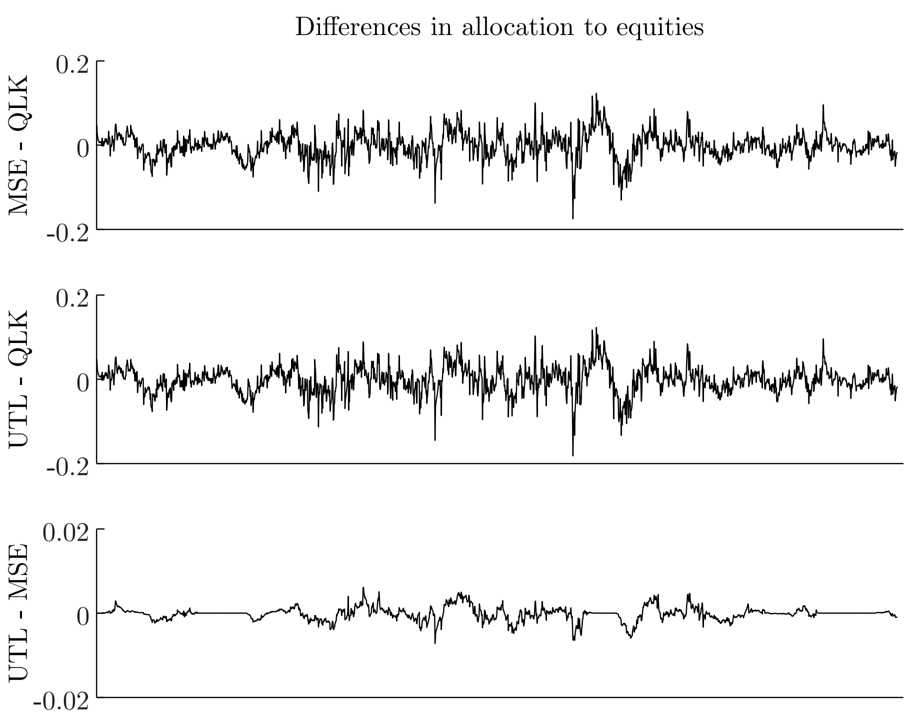

Figure 4: Differences in allocation to equity implied by MSE and QLK forecasts (top panel), UTL and QLK (middle panel) and MSE and UTL (lower panel).

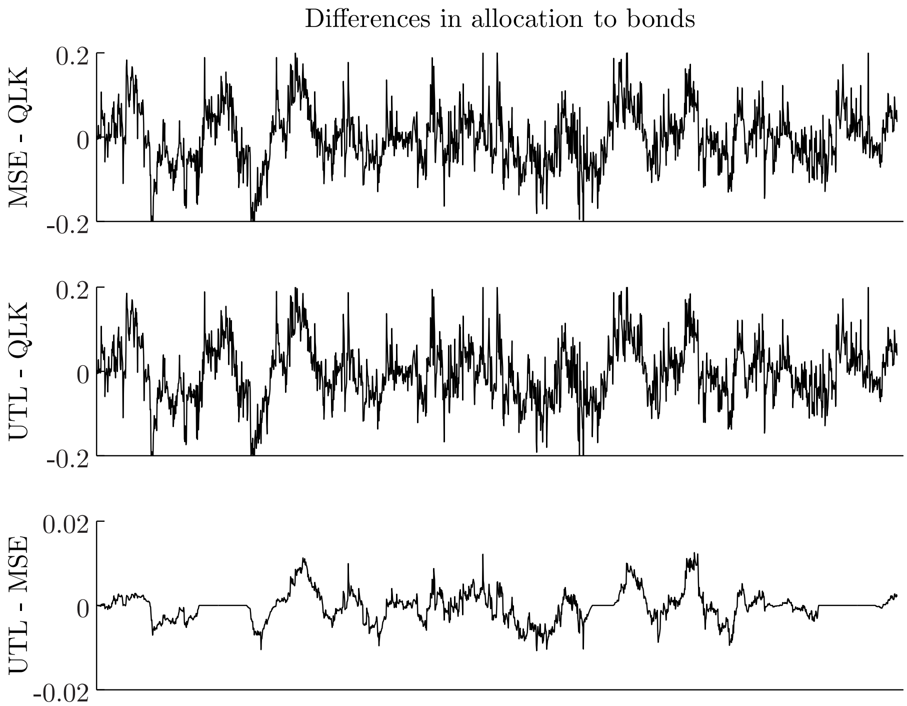

Figure 5: Differences in allocation to bonds implied by MSE and QLK forecasts (top panel), UTL and QLK (middle panel) and MSE and UTL (lower panel).

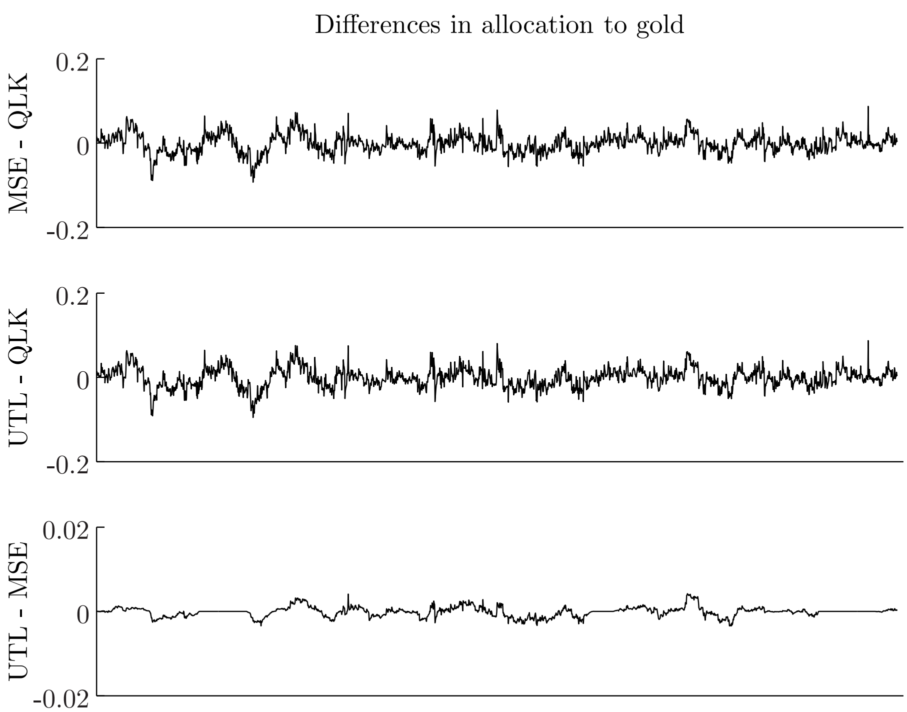

Figure 6: Differences in allocation to gold implied by MSE and QLK forecasts (top panel), UTL and QLK (middle panel) and MSE and UTL (lower panel).

The final dimension along which the results will be considered is the relative economic value of the forecasts captured by Δ in equation 4. In doing so, we attempt to capture a degree of uncertainty in expected returns. Apart from $\mu = [3.12; 2.69; -9.45]$, a number of combinations of expected returns for equities and bonds have been considered. $\mu = [6; 3; -9.45]$, $\mu = [9; 3; -9.45]$ and $\mu = [12; 6; -9.45]$ have been chosen to reflect larger risk premia on both bonds and equities along with a larger spread between bonds and equities. Values for Δ reported below will show the range across the assumed values for μ.[4]

Table 1 reports the ranges for values for Δ representing the relative economic benefit of using the loss function in the column heading over that in the row heading (expressed in annualized basis points). They are reported for $\gamma = 2$, 5, 10 and transactions costs of 1 index point. For all combinations, both MSE and UTL are preferred over QLK. In terms of relative economic benefit it ranges between 16 to 21 basis points. In contrast, the range of Δ for differences between MSE and UTL are very small in comparison and contain zero. The result that MSE and UTL lead portfolios generating similar economic benefits is once again consistent with earlier results in relation to similarities in portfolio allocations and parameter estimates.

	$\gamma = 2$		
	QLK	MSE	UTL
QLK		16.955 – 20.927	17.373 – 21.101
MSE			−0.185 – 0.416
UTL			
	$\gamma = 5$		
	QLK	MSE	UTL
QLK		16.787 – 20.605	17.192 – 21.747
MSE			−0.222 – 0.403
UTL			
	$\gamma = 10$		
	QLK	MSE	UTL
QLK		16.491 – 20.044	16.668 – 20.130
MSE			−0.275 – 0.385
UTL			

Table 1: Ranges for Δ, the relative benefit of using the estimation criteria in column headings instead of that in row headings, expressed in annualized basis points. Transactions costs are a bid-ask spread of 1 index point. Coefficient of risk aversion is $\gamma = 2$ (top panels), $\gamma = 5$ (middle panels) and $\gamma = 10$ (lower panels).

The results of this paper build upon those of Fleming, Kirby and Ostdiek (2003) in showing that beyond the choice of data, the choice of loss function is also important in the context of portfolio allocation. The UTL loss function, consistent with how forecast performance is measured in the portfolio allocation context, dominates traditional QLK and supports the findings of Skouras

[4] A full bootstrap type replication scheme such as that employed by Fleming, Kirby and Ostdiek (2003) is not computationally feasible here due to the UTL approach needing to be re-estimated for each value for μ.

(2007). However, one can generate forecasts, and hence portfolios of equivalent economic benefit by using the statistical MSE loss function.

6 Conclusion

Forecasts of volatility are important in many aspects of finance, and as such this literature has grown substantially in recent years. While volatility models are traditionally estimated within a statistical framework, the forecasts they generate are often used or evaluated in economic applications such as portfolio allocation. While this is the case, there is little understanding of the differences between models estimated on either a statistical, or directly on an economic basis and finally applied to a portfolio allocation problem. This paper seeks to gain a deeper understanding of how models estimated under both statistical and criteria perform in the portfolio allocation setting.

Within an negative exponential utility framework, it is found that economic benefit accrues from estimating the parameters of a volatility model under an economic loss function relative to a likelihood based approach. This result is consistent with earlier research that indicates gains are to be had by estimation using the economic criteria under which the model will be applied. As opposed to a statistical forecast of volatility being used to form optimal portfolios, an investor would prefer to estimate a model of optimal allocations as a direct function of historical data. However, it is found that one can virtually replicate the benefit of utility based estimation by the use of a mean squared error estimation criteria. Overall these findings have direct implications for the manner in which volatility models are estimated when used within a portfolio allocation framework.

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